WHY BUSINESS FAIL

A prediction model for SME's failure in Greece

Master thesis for the Executive MBA,

International Hellenic University

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ABSTRACT

Business failure is one of the most common terms heard today when the current economic crisis in Greece is brought up. It can be characterised as a company's inability to cope with its obligations to its creditors, or in other words, its inability to pay its debts. Internal and external factors such as management efficiency, competitors, and funding ability may all lead to the risk of bankruptcy.

Indications of a possible corporate bankruptcy are apparent well before the real bankruptcy takes place. As a result, designing models that forecast imminent financial collapse has become an important aspect of corporate finance literature in order to assist management in refocusing their resources, re-evaluating their corporate strategies, and eliminating losses. This work explores the literature on predicting financial distress and decision making as well as assessing the probability of bankruptcy based on solvent Greek SMEs during the period 2014 to 2019 via logit analysis.

To do so, we'll look at a sample of bankrupt and non-bankrupt companies, as well as a collection of economic and financial ratios. These ratios are determined using the data from the firms' balance sheets and income statements. This financial analysis, which is calculated using the ratios, is necessary to evaluate how healthy the company is financially, therefore assisting investors, creditors and managers when predicting favourable situations or economic difficulties.

In this analysis, a four-variable Logit model developed via a forward-stepwise selection protocol correctly predicted 83% of 92 matched-samples one year before default.

Keywords: Business failure, Logit Analysis, Bankruptcy prediction, Statistical Analysis

ACKNOWLEDGEMENTS

My wife and sons, Vaso Zanidou, Christos and Aggelos, for being a source of inspiration for me and a reminder of what I've done.

To my supervisor, Professor Stergios Leventis, for his academic guidance, valuable assistance, and constant encouragement during this thesis.

Special thanks, to the School of Humanities, Social Sciences and Economics Board and Staff for their kind operational and financial support.

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1. INTRODUCTION

1.1 Background

Small and medium-sized enterprises (SMEs) in Greece play a major position in Greece's 'non-financial market economy'. They account for 63.5 % value added and have an unusually high job share of 87.9%. Greek SMEs hire 2.6 workers on average, which is approximately one-third less than the European union average of 3.9 ((SBA), 2019) and have suffered disproportionately as a result of the crisis, unable to deal with shifting spending habits and unavailable credit (Pearce, 2006). Business failure is a typical occurrence for business owners (Pratten, 2004), and it is the most possible result for new businesses, but there is little awareness of whether and how it occurs. Lack of analysis into market loss is due to a lack of reliable evidence. Such studies, on the other hand, will offer useful insights into the conditions needed for small enterprises to succeed in economically difficult times, as well as help in the development of government support strategies (Chittenden, 1993). (Abdelsamad & Kindling, 1978) endorse this view: "*while failures in a free enterprise system cannot be entirely prevented, the rate of failure can be decreased if some of the triggers are detected and preventative measures are taken*".

An early and precise indicator of bankruptcy will assist companies in taking the required measures to overcome their financial difficulties. By applying a bankruptcy forecast model for the Greek market, Greek companies may be able to reduce risk and escape bankruptcy.

1.2 Purpose and Hypothesis

According to (Giannopoulos, 2019) the majority of the bankruptcy prediction literature has focused on the United States and the United Kingdom, there have also been models developed for Greek companies. (Grammatikos, T. and Gloubos, G., 1984) developed a series of linear probability, Probit, logit, and multi discriminate analysis models for Greek firms. The Probit and linear probability models were the most accurate of the proven models, with 70.8% accuracy. For Greek manufacturing firms, (Theodossiou, 1991) developed a linear probability model, a logit model, and a Probit model. The linear likelihood model was the most accurate of these models, with a 96.4% accuracy. (Dimitras, 1996) developed three separate models for

Greek companies: a rough set theory model, a multi discriminate analysis model, and a logit model. All three models were accurate one year before bankruptcy, with the rough set theory model being the most accurate (73.7%). (Zopounidis, 2002) developed a utilities additives discriminant model that used twelve different ratios that had an accuracy range fρομ 47.37% to 84.21% for distressed firms. The models described in this section were created and used prior to the financial crisis of 2008. This study attempts to investigate whether the logit analysis model performs well on a more recent (post-financial crisis) sample date. As a result, the following hypotheses are being investigated:

Hypothesis: Financial ratios can be used to forecast Greek business bankruptcy.

This hypothesis examines whether bankruptcy in the Greek economy can be forecast by analysing the ratios of various SMEs.

1.3 Key concepts definition

1.3.1 Definition of failure

Much philosophical debate has centred on the various ways in which market loss can be described. The concept is important because it can emphasise certain consequences while missing others. Failure is commonly described as the discontinuance of a company due to a lack of sufficient financial capital (Everett, 1998) and "*involves liquidation of insolvent companies and personal bankruptcy*", except market closures where the company may have managed to survive (Burns, 2007, p. 340). (Fredland, 1976, p. 7), nevertheless, suggest that dissolution of a business can be used as a "*proxy for failure*", as "*discontinuance suggests that resources have been shifted to more profitable opportunities*". Cochran is of the realistic belief that "*failure should mean inability to 'make a go of it' whether losses entail one's own capital or someone else's*" (Cochran, 1981, p. 52). (Watson, 1996) defined five types of firms failure: ceasing to exist (for whatever reason); closing or changing ownership; declaring bankruptcy; closing to reduce losses; and failing to meet financial targets. While several businesses close due to a profitable acquisition (Bates, 2005), many more do so because the company has become insolvent (Politis, D. & Gabrielsson, J., 2009).

According to (Longenecker, 1999), some definitions focus solely on the fact of ceasing to trade, while others recognise a more human sense of inability to run a company in a manner that will enable it to operate sustainably. This study defines failure as any kind of termination, whether by bankruptcy, liquidation, loss avoidance, demerger, acquisition, or takeover, and/or dissolved due to personal decision.

1.3.2 Insolvency in Greece

The term insolvency is frequently used to talk about the actual economic crisis. This term denotes a company's inability to fulfil its commitments to its creditors, i.e., the inability to pay its debts. To understand if a company is in this type of situation, it is necessary to prepare an analysis of its economic situation. On one hand, a company can be insolvent because it is unable to meet its obligations by lack of access to credit or by illiquidity, but on the other hand, a company can be suffering a particularly financial difficulty that is preventing it from settling its debts on time.

According to paragraph 1 of Article 77 of the "Debt settlement and second chance and other provisions." (Law 4738/2020), it is considered bankrupt when a debtor who is in arrears or is unable to fulfil his overdue payment commitments on a long-term and general basis. Payments made through deceptive or harmful means do not fulfil any commitments.

There are some stages before the company can be declared insolvent and the bankruptcy process requires some deadlines so that a company can be declared as bankrupt. The first stage consists on the evaluation of the economic situation. Being insolvent indicates that a firm is unable to fulfil its commitments, but the disability must be certified at one point through the declaration of insolvency. This statement can be accomplished by two criteria:

1. The criteria for cash flow (cash flow)
2. The criterion of the balance sheet or asset (balance sheet or asset)

The first criterion means that the debtor is insolvent, so it becomes unable, through lack of cash, to pay its debts when they fall due.

Regarding the second criterion, insolvency arises from the fact that the debtor's assets are insufficient for full compliance with its obligations. This analysis can become truly complex since it is sometimes difficult to know the true value of the debtor's assets.

This bankruptcy may be required by the company days or months after failing to comply with at least one material obligation capable of notifying inability to resolve the majority of its obligations.

It is worth noting that the company managers are not the only ones who can start the insolvency proceedings. Firstly, this responsibility falls to the debtor, and if he is not able to do this process, it follows to the legal representative. In addition, the debtor has legacy to submit for insolvency to any creditor. The prosecutor can also file a case of bankruptcy of a company (if the debtor is unable to solve their financial problems, in case of leakage of the holders or abandonment of the seat of business, or in a situation of dissipation or goods loss).

When a possible bankruptcy is diagnosed, it is important to define how the company will overcome it. This can be done in two ways:

- Survive (2nd change and debt restructuring)
- Notify for insolvency problems

It thus appears that after entering in financial difficulties, a company should try the extra-judicial settlement. This is more economical and presents less costly alternatives. This implies unanimity among creditors and the intention to ensure business continuity. If this alternative is successfully achieved, then the company's survival is ensured. If it happens otherwise, the company will have to go into insolvency proceedings via the judicial solution.

1.4 The thesis's overview

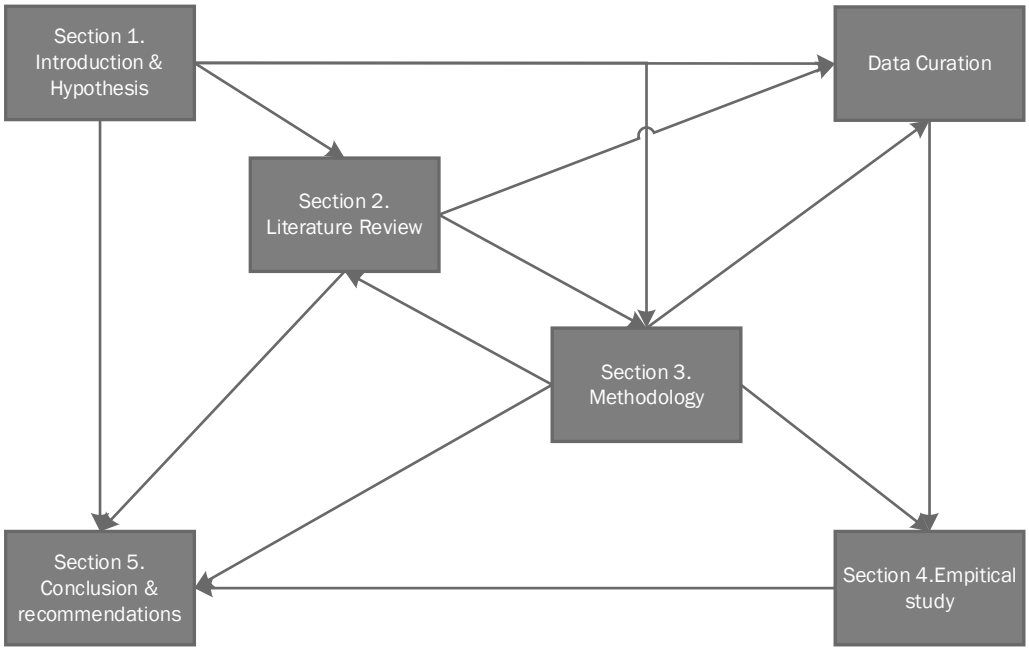

Figure 1: Thesis outline

2. LITERATURE REVIEW

The literature review serves as a tool to help draw on previous work. To maintain high up-to-datedness, we will concentrate on scientific publications with the most recent publishing date, with certain exceptions for importance and consistency. Textbooks can be seen in proportion to their current importance as a medium for acquiring awareness of basic principles and hypotheses in the field of accounting. Sources contained in online articles and via a free Google search will be considered additional content if they supplement, encourage, or enrich the text.

There is a distinct absence of high-quality journals around business failure. In comparison to scientific search engines, a search on Google.com with a keyword like business failure yields 617.000.000 hits in 0.57 seconds (2021-02-22, 18:25). When it comes to bankruptcy and forecast models, the challenge in locating accurate information is mitigated. Greek researchers such as (Dimitras, 1996), (Giannopoulos, 2019), (Grammatikos, T. and Gloubos, G., 1984), (Theodossiou, 1991), (Zopounidis, 2002) make up the base for this thesis research. We might argue that these writers are "pioneers" in the field of business failure and bankruptcy forecasting, at minimum from a Greek standpoint, and that by researching business failure, we can deviate from their research direction and, ideally, expand this area of bankruptcy prediction.

2.1 Business Failure

2.1.1 Internal Failure Factors

It is important to note that (Lehmann, 2005) emphasises the importance of recognising businesses in financial trouble, despite the fact that research in the field of company loss is small. They consider this to be an important field of study and observation.

(Pompe, 2005) examined evidence from small and medium-sized manufacturing firms to forecast bankruptcy, and their findings indicate that it is more difficult to predict bankruptcy in young companies than that in large companies. This is intriguing because we are involved in businesses that have progressed beyond the start-up stage in our thesis. Furthermore, according to (Pompe, 2005), the explanation for this is that a long fall into bankruptcy is less possible, and therefore the bankruptcy is much more unexpected. The study discovered that the ***cash***

flow/total debt ratio achieved the highest average accuracy for both old and new firms. In the negative side, we find that this report focuses on manufacturing firms, and another criticism is that they do not present the root reasons of why companies fail, which may have been fascinating.

To proceed, (Stokes, 2002) emphasise that a closure/failure mechanism should be constructive in the sense that it can be instructive. One of their findings is that many models have been designed to deter and escape failure, and that they give the appearance that failure is always bad and cannot be learnt from. Furthermore, while looking at studies in this field, (Stokes, 2002) discovered that failure occurs in three distinct fields. These are i) the founder's personal characteristics; ii) the company's strengths and strategies; and iii) ultimately, the business environment's circumstances. One of the authors' observations were that many entrepreneurs who close their businesses are eager to reopen them because they believe they will be better prepared to manage situations in the future as a result of the lessons learned from the previous closing. Another inference is that previous research has linked dissolution to loss, and that termination is often correlated with failed projects. For this thesis, failure refers to bankruptcy.

According to (Lehmann, 2005), business failure is the result of several choices and decisions taken within the particular organisation. To bolster this argument, and by an article in (Direction, Strategic, 2005), the word "failure" is often defined as the product of bad decision-making. In addition, "*often the wrong model is adopted for a strategy despite the most careful planning because assumptions are made that could easily prove incorrect*" (Direction, Strategic, 2005). The final argument is the importance of preparing for the unexpected; ''*Any manager asked to provide a prediction regarding performance, is put in an invidious position*'' (Direction, Strategic, 2005).

The article even states that corporations have never invested this much time, effort, and resources on market analysis and intelligence, and despite this, the number of failed enterprises has not decreased. The loss rate is more likely to have risen. This argument raises the question, "*Have we experienced nothing?*". This study highlights the value of undertaking a more in-depth inquiry into business failure.

(Lehmann, 2005) stress the relevance and urgency of their work by referencing recent management accounting incidents that have shaken the corporate community. They go on to state that it is important to develop company staff competencies in the area of business failure.

The findings of Lehmann and Norman's work do not offer a solution to the issue of business failure, nor do they clarify why it happens, but they do provide necessary resources for identifying businesses in financial distress. According to the findings, experts submit less detail and perform less assessments during the identification period than mid-level staff. Moreover, by supplementing conventional instructional knowledge with technical approaches (Lehmann, 2005).

(Richardson, B., Nwankwo, S. and, Richardson S., 1994) address in their article how businesses often struggle due to a shortage of funds. The most common explanation for this is that they are unable to stay competitive and therefore struggle to retain consumers and other suppliers.

There is a connection between product innovation and customer attraction, but innovation can also cause problems. As per (Min, S., Kalwani, M. and Robinson, W., 2006), a pioneer who offers a truly novel product will face significant challenges if only to survive. Business pioneer survival costs are much smaller in markets begun by gradual innovation. The results show that a new product, especially if it is the first product to enter a market, is always the first to fail. Survival is made more complex by the unusually high prices and risks. An early follower, on the other hand, will learn from the pioneer's errors and stop repeating them.

The writers explain the advantages and pitfalls of being the first in a foreign market in a reasonably detailed manner. However, they do not have any answers to the issue of when a follower can reach the market. Entrepreneurs struggling because they were pioneers are unlikely to be a frequent occurrence among the SME's in this analysis; with the exception that it occurred just after the Greek economy's recession and that they immediately reversed their policy and perhaps introduced a new product or service as a result. Even, if this is our view, it should be said that if a company is to succeed over time, it must reinvent itself while being as self-sufficient as possible (Hamel, 2000).

2.1.2 Management Failure Factors

In "*Understanding the causes of business failure crises*", (Richardson, B., Nwankwo, S. and, Richardson S., 1994), divide various forms of market loss into frogs, a term used by (Richardson, Bill & Nwankwo, Sonny & Richardson, Susan., 1994), so that the reader can differentiate between them. In the paper, there is a table that categorises organisations as **boiled**, **drowned** and **bull frogs**, as well as **tadpoles**.

Boiling frog failures occur as organisations are slow to implement new things and therefore cannot keep up with the environmental change. Any of the causes of the boiled frog syndrome include top management's ignorance to modern and diverse company natures, increasing "white-collar" prices, and poor employee morale. We are especially interested in the topic of ongoing disruption, as well as the rapid and global transition in technology that impacts the majority of companies.

The drowned frog is a second form of company failure. A drowned frog feels the urge to be everywhere at once, which leads to the frog sinking of its own creation. The business that is in this predicament lacks free space and does not have protection. In an organisational context, the drowned frog reflects a failed visionary entrepreneur, while in a larger market, it is a conglomerate leader. In the drowned frog scenario, the causes of business failure are one-man supremacy, "he knows it all," and a non-participating board that works with the one man rather than for him.

Bullfrogs are the third group, and they are show-offs. The bullfrog puts a high emphasis on status and strength. Tadpoles, on the other hand, are abandoned start-ups that will never become frogs. We're not interested in tadpoles. Any of the reasons for failure are that businesses are often too confident about their own goods, market volumes and sales rates, real costs relative to real earnings, and so on. The study provides a comprehensive viewpoint on the causes for weakness among the various classes, but that is still what it does. Any of the reasons for failure are that firms are often too confident about their own goods, market volumes and sales rates, real costs relative to real earnings, and so on. The study provides a comprehensive viewpoint on the causes for weakness among the various classes, but that is still what it does. It emphasises on person-specific features, which may be useful, but only for the issues mentioned

by the writers in the paper. The analysis does not provide a wider viewpoint on things, nor does it provide a broader view of how these things are interconnected.

2.1.3 External Failure Factors

(Cope, J., Cave, F. And Eccles, S., 2004) begin their article by stating that business failure is a significant outcome of entrepreneurial practice, but it is a widely underdeveloped field of study. The paper is fascinating, since it is written from the viewpoint of a venture capitalist; an investor's curiosity in companies who have been involved in a prior market disaster. This article includes fascinating details about the relationship between formerly effective entrepreneurs and those who will fund their return, give them a second chance, and encourage them to exploit new opportunities once more. This may be moving the analysis a step forward, which is not our focus, but this paper also emphasises the role of external factors in the failure process and demonstrates that venture capitalists should not always fault the entrepreneur.

(Hemraj, 2004) on the other hand, is concerned with bank loans and their effect on enterprises. He continues to investigate the causes of company loss and what should be done to prevent them from happening again. According to (Hemraj, 2004), business failure is often caused by borrowing capital from a bank for non-viable investments, merely being an immature borrower, using short-term borrowing for long-term financial needs of the business, borrowers not being in the right market at the right time, and borrowers not making enough money to repay their loans. Finally, (Hemraj, 2004) emphasises the significant effect of lenders on business failure. In our opinion, there has been further debate about the failure of small and medium-sized enterprises (SMEs) to obtain a bank loan. (Hemraj, 2004) appears to be of a different belief, claiming that lenders are unconcerned with how well borrowers run their businesses, what they borrow for, or whether they have ever been profitable. Lenders are solely concerned with the certainty, and if they are convinced that they will be paid back, they will not hesitate to lend money. (Hemraj, 2004) emphasises that all lenders and creditors must behave in accordance with viable industry, and he goes on to state, "*It is high time that judges penalise lenders who depend entirely on guarantors, rather than viable firms, to repay the loan.*". The notion that obtaining a bank loan may be too convenient contradicts our belief and experience, since we are constantly told that borrowing is an impediment for SMEs.

According to (Cope, J., Cave, F. And Eccles, S., 2004), venture capitalists are very accommodating, agile, and open-minded when it comes to business failure. They are frequently curious about the conditions behind the loss. The entrepreneur is often not regarded as the prime cause of a company's downfall (Cope, J., Cave, F. And Eccles, S., 2004). In summary, prior failure would not have a major effect on the decision to spend more or new funds in an entrepreneur; the entrepreneur is not even the most relevant consideration in the venture capitalist's decision-making process. Business loss is often caused by external forces that are beyond the entrepreneur's and venture capitalists' influence (Cope, J., Cave, F. And Eccles, S., 2004).

For instance, (Pearce, 2006) highlight a potential external factor, namely the negative effect of a recession on company business. According to the authors, while this is real, relatively few professionals and researchers understand how to plan for and adapt to problems after an economic crisis. Furthermore, as will be discussed further down on this page, a recession is more painful if you have recently lost a large client (Harding, 2005). If possible, we will put this relationship to the test in our study.

(Pearce, 2006) proposes a plan of action to assist in dealing with the effects of the recession. A solution to this issue of failure was not what we were looking for, however this article provides an interesting insight into how a global "problem," such as a recession, affects businesses all over the world. Recessions are said to account for a large portion of our economy's complexity. We don't know where we're going, but we do know that financial crises drive change. (Pearce, 2006) believe that recessions can be beneficial because they create new opportunities. The supply of capital used by businesses is significantly influenced by "creative destruction," as it is often referred to, but firms that are better at conserving, sustaining, and retaining resources compared to rivals can strengthen and draw on their competitive edge. According to the writers, the conventional approach to dealing with an economic crisis, which is to cut costs in whatever way possible, is not the most successful way to deal with the situation. According to (Pearce, 2006, p. 208), "reducing R&D costs, reducing customer support, and laying off staff can have the desired impact of increasing near-term performance, but they increase the risk of irreversible harm to competitive advantage and market share growth." Too drastic a reduction in valuable business "capital" can result in potential business failure.

Even though the issue of money shortage should be classified as an internal factor, there are other causes, often external forces, that affect this money shortage. (Harding, 2005) discuss many causes of sales decline. They talk of the threats. The first threat is putting all of your eggs with one basket. The customer risk and the business risk are also present here. In the first case, the risk of getting very few customers, and in the second case, the risk is having more of the clients in the same industry. The second risk is when a company has too few hens; when one of the hens fails, no further eggs can be made from that source, resulting in a loss of profits for the company. A third risk is trend; the risk that something is very popular at one point, but then rapidly declines in popularity. The standard period risk is a fourth risk; a contraction hurts more if you recently lost a large customer.

(Harding, 2005) discuss some of the issues that businesses face. They do not provide a comprehensive view of the subject; rather, they just scratch the surface. Increased diversification and increased reserves, according to the authors, are the solutions to the problems associated with various types of risk. Firms really should focus more on risks, but while it is reasonable to believe that they must focus more and diversify more, the authors provide no exemplars of how this could be accomplished.

2.2 Bankruptcy Prediction

Dun & Bradstreet (D&B) has embraced the idea of company failure, which involves businesses that ceased operations due to dissolution or bankruptcy, resulted in a liability to creditors, and willingly withdraw, leaving unpaid debts, which were embroiled in legal proceedings such as receivership, reorganisation, or settlement.

As per a bankruptcy statistics survey by the Hellenic Statistical Authority (ELSTAT), there were 474 liquidations in Greece in 2011 on the peak of the Greek debt crisis, with an increase of 24.7% compared to the same period the year before. Figure 2 shows the number of company liquidations in Greece from 2008 to 2017. The average number of liquidations is above 300 per year.

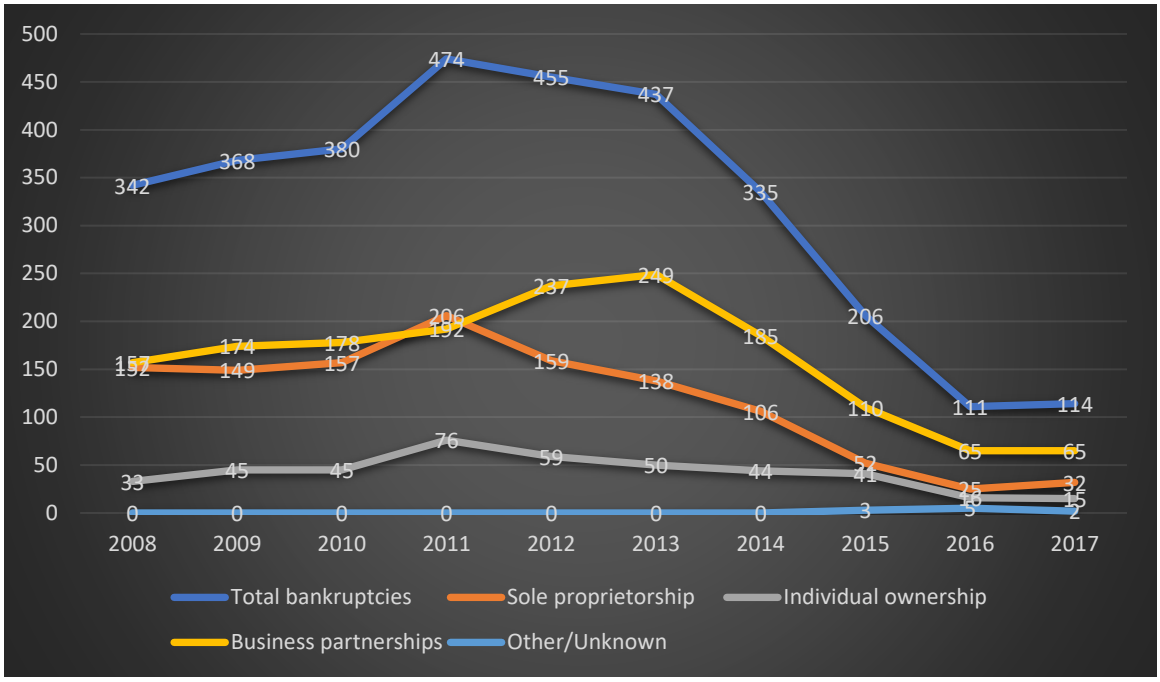

Figure 2: Companies declared bankrupt by legal form, 2008 – 2017

(Source; The Hellenic Statistical Authority (ELSTAT) statistics on Business Bankruptcies on the basis of the bankruptcy court orders issued for the year 2017, 13th, April 2019)

In a highly competitive market climate, a company's health is dependent on:

1. When it was established, how financially sound it was;
2. Its ability to produce cash from ongoing activities, as well as its relative versatility and efficiency;
3. Accessibility to capital markets; and
4. When confronted with unanticipated cash shortages, its financial potential and staying power.

A company eventually reaches a danger zone as it becomes increasingly insolvent. In order to remain solvent, the corporation must then boost its activities and capital structure. According to Dun & Bradstreet statistics, the following five reasons contributed to market failures: (1) financial, (2) management background, (3) declining revenue, (4) increased expenditures, and (5) other unspecified considerations are depicted in Figure 3 below. According to the data in

Figure 3, economic conditions are the leading cause of company failures, followed by management experience.

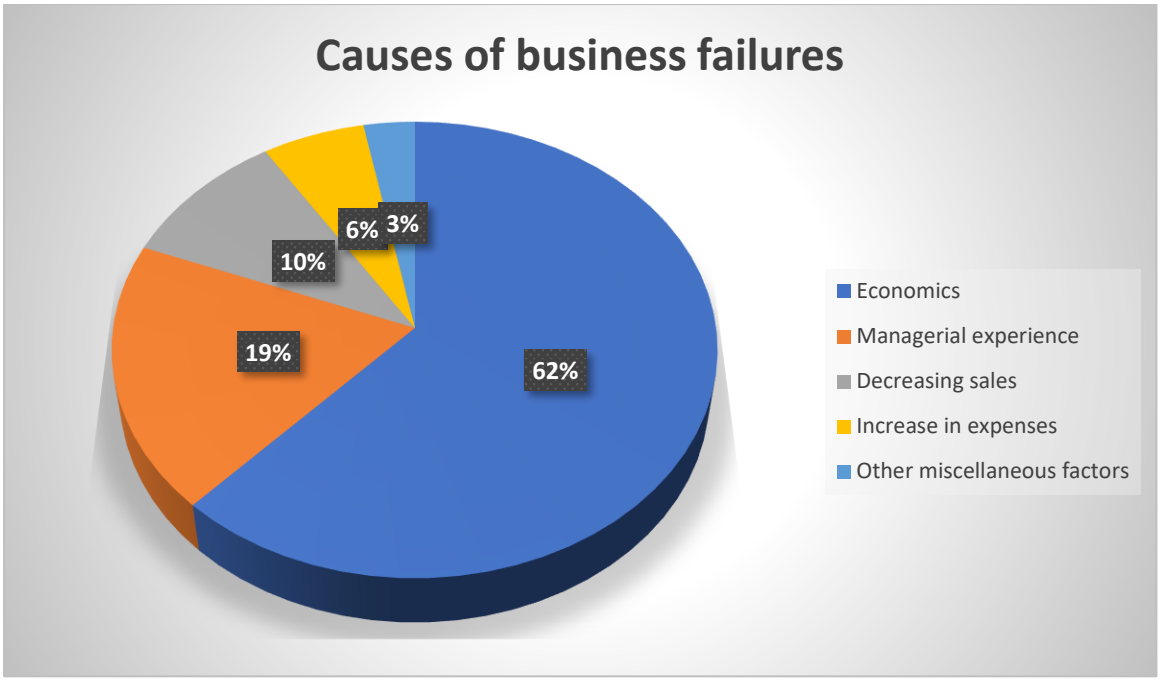

Figure 3: Causes of business failures

Various approaches or predictors of the incidence of bankruptcy incorporation have been studied in company failure studies. The methodological approach attempts to determine why a group of businesses failed in the past and why a related group of businesses succeeded. Furthermore, the statistical technique's aim is to find indicators that can often correctly predict imminent failure. Models for forecasting bankruptcy have been developed using a number of statistical techniques. Univariate regression is the most often used (Beaver, 1966), analysis of multiple discriminants (Altman, 1968), Logit (Ohlson, 1980) and Probit analysis (Zavgren, 1983), partitioning in a recursive manner (Frydman, 1985) and neural networks (Coats, 1993). These approaches aim to define a series of financial ratios that it is possible analysed to assess the probability of a company's failure. Furthermore, most observational studies that aim to reliably predict failure have a substantial decrease in predictive accuracy more than two years before failure.

According to (Altman, 2011), four common concepts have been used when addressing financial instability in businesses: failure, solvency, bankruptcy, and default. When a corporation "*cannot fulfil its current obligation*" it is referred to as being in financial distress. (Altman, 2011). When this happens, a company's debts are usually raised to support the payments. If a company fails to make regular loan and/or bond payments, it enters into a statutory default and must apply for bankruptcy.

The cost of financial distress may be categorised as direct or indirect. Direct expenses are considered out-of-pocket expenses by accountants, turnaround experts, lawyers, expert witnesses, and other professionals. Both unobservable opportunity costs are called indirect costs. These expenditures include all lost revenue and income as a result of consumers declining doing business with a firm that is about to file for bankruptcy (Altman, 2011).

(Hunter, 2001) argue that the failure to settle loans as they become due is the basis of business upheaval and destruction. Gearing and a shortage of liquid assets are two factors that lead to a company's inability to pay its bills.

(Poston, 1994) identifies five levels of market collapse. The phases are as follows: (1) incubation, (2) financial humiliation, (3) financial insolvency, (4) absolute insolvency, and finally (5) reported insolvency. During the first point, as financial issues began to surface, the company will most likely go unnoticed. In the second level, the company's executives, as well as those in the organization, would become aware of the company's problems. This is the point at which the company is unable to satisfy its commitments, despite the fact that its assets outweigh its liabilities. Even though the corporation has assets, those assets cannot be used to make payments because they cannot be liquidated.

When a company is unable to collect the requisite money to fulfil its commitments, it reaches the financial insolvency period of corporate loss. At this stage, there are still businesses that have been restored to fitness. Companies who are unable to return to a stable state, on the other hand, proceed to the fourth stage which is the complete insolvency. As mentioned by (Fitzpatrick, 1934) cited in (Poston, 1994) the fourth stage "*occurs when the liabilities exceed the physical assets. It is, in several instances, when the public and creditors who have not yet*

been told of the company's true financial state hear that the company is failing. The organization can no longer stop acknowledging its loss".

At the fourth step, absolute insolvency, creditors could take over the business or restructure the distressed debt. In addition, the organisation will seek external financing from a number of sources. If none of these approaches succeed, the company reaches the fifth and final level, the confirmed insolvency. This step entails taking court steps to protect the company's creditors. This is the point at which the corporation announces bankruptcy. The majority of companies that enter this level are liquidated, but others are restructured and reorganised and restored to a stable state.

Failure is characterised as a company's inability to repay its creditors, vendors, preferred stock owners, and other creditors, or when a bank balance is overdrawn, or The corporation has been declared bankrupt by legislation. All of the above circumstances result in the company's activities being halted (Dimitras, 1999).

(Taffler, 1983) said that financial indicators or signs may be analysed to forecast bankruptcy or organizational failures, according to the author. Looking at the firm's financial statements over the course of specific time window will show the signs or indicators (Slatter, 1984) and (Hunter, 2001).

(Altman, 1968) said that financial ratios should be used to identify whether an organisation is undergoing operational and economic difficulties, according to the author. The use of financial ratios to determine a company's profit growth, liquidity, leverage, turnover, volatility, and size provides the audience with a detailed understanding of the market (Leksrisakul, 2005). (Beaver, 1966) financial ratios analysis has discovered that using financial ratios can forecast financial distress five years before bankruptcy.

Several experiments have been performed over the years that used various ratios to forecast bankruptcy. Based on (Bellovary, 2007) the literature on bankruptcy prediction goes back to the 1930s.. In 1930, the Bureau of Market Research conducted a report in which eight ratios were found to be successful indicators of failing businesses. For the next 30 years, models for forecasting bankruptcy depended on univariate or single factor regression to predict potential loss. Person ratios may be deceiving and insufficient in predicting bankruptcy. (Altman, 1968)

was the first time a multivariate discriminate analysis model was written. Altman's Z-score model calculates a Z-score based on five financial ratios, which distinguishes between a *healthy* and *unhealthy business*.

There were two other models built during the 1960s, additionally to the Altman's Z-score model. Following 1960, a slew of new models appeared. In the 1970s, 28 studies were written, followed by 53 studies in the 1980s and 70 studies in the 1990s. At the time of 2000-2004 there were 11 studies published (Bellovary, 2007). Since these experiments concentrate on various study areas, the models involve a different number of ratios. (Ohlson, 1980) implemented a logit analysis, (Zmijewski, 1984) implemented a Probit analysis in the study. Other models that have been applied are (Altman, 2011) neural networks, (Erik M. Vermeulen, 1996) multi-factor model and (William F. Messier, 1988) expert system model. These models are used by auditing services, securities consultants, insurance providers, insurers, and financial institutions; *i.e.* see (Poston, 1994) and (Dimitras, 1999).

To predict company bankruptcy, models have been developed that use a variety of ratios. Compared to Altman's Z-score, which analyses company bankruptcy using five different ratios (Jo, 1997) in their multivariate discriminant analysis, they use as many as 57 different ratios. The use of more ratios in a model does not necessarily indicate that it is more accurate. For example (Jo, 1997) model is 81.94% accurate, whereas (Rose, 1985) model which uses 23 different ratios is 76% accurate and (Moses, 1987) model, which employs three different ratios, is 85% accurate. The competing models are listed in detail in Table 1.

The models that have been built have been produced for several industries, including manufacturing, banking, airline, small business, such as oil and gas, etc. Furthermore, the models were produced for particular countries; (Grammatikos, T. and Gloubos, G., 1984) have developed a model for Greek companies, (Taffler, 1983) were focused on UK manufacturing companies although (Rose, 1985) banks were expected to go bankrupt. Other versions, such as, were created for general use (Gordon V. Karels Arun J. Prakash, 1987).

Table 1: Details for the competing models

	Application Study Period	Criteria for failed company	Timeframe	Model Accuracy
Altman model	33 failed and 33 non-failed US manufacturing companies 1946-1965	Company that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act	5 years	76% for hold-out sample
Taffler model	23 Failed and 45 non-failed UK industrial companies, 1968-1973	Receivership, voluntary liquidation, winding up by court order or equivalent	4 years	96% for failed companies and 100% for non-failed companies
Grammatikos and Gloubos X model	29 failed Greek industrial companies and 29 non-failed companies, 1977-1981	Went bankrupt or applied for bankruptcy	3 years	93% for failed companies and 90% for non-failed companies
Grammatikos and Gloubos Y mode	29 failed Greek industrial companies and 29 non-failed companies, 1977-1981	Went bankrupt or applied for bankruptcy	3 years	90% for failed companies and 93% for non-failed companies
Dimitras et al. model	80 Greek companies, 40 failed companies and 40 non-failed companies, 1986-1990	Went bankrupt or applied for bankruptcy	3 years	Hold-out sample: Year 1: Failed companies: 63.2% Healthy companies: 68.4%
Zopounidis and Doumpos model	58 Failed and 58 non-failed companies.	Failed companies	3 years	Hold-out sample Year-1: 65.79% Year-2: 57.89% Year-3: 55.26%

(Source; Prediction of Bankruptcy Using Financial Ratios in the Greek Market, George Giannopoulos, Sindre Sigbjørnsen, 29th, April 2019)

3. METHODOLOGY

3.1 Data & Sample Selection

We selected 1256 samples (1000 active and 256 bankrupt) from the AMADEUS (Analyse Major Database for European Sources) database, are Greek SMEs spread around the country with last year of operation from 2014 to 2019.

The data sample consists of 92 businesses, with 46 in each of the two categories. Companies in the delinquent class - Group 1 - have filed a bankruptcy claim under Greek legislation and last year of operation varying from 2014 to 2019. In theory, we would like to analyse a set of ratios at time **t** in order to make projections for firms in the future (**t+1**). This was not possible to investigate due to data constraints. Recognising that this category is not fully homogeneous, we attempted to pick nonbankrupt firms with caution.

Group 2 is made up of firms selected at random on a heterogeneous basis. The businesses are classified according to their size. Group 2 firms were operating at the time of the study. Furthermore, the records used come from the same years as those used to process the bankrupt firms. The data for the study test was obtained from financial statements dated one annual reporting cycle before bankruptcy.

According to a common assertion, financial ratios, by definition, deflate figures by scale, removing a significant portion of the size effect. The logit model, which will be discussed further below, tends to be fairly stable to support large corporations.

The logit model included major distressed firms and is undoubtedly applicable to both small and medium-sized enterprises.

3.2 Variable Selection

For bankruptcy prediction, a total of 23 variables are chosen. Five of them are overlooked due to a lack of data. Thus, there are 21 variables selected from each sample company's financial statement in four categories, as seen in Table 2, which include organizational performance, profitability, management structure, and human resources, among others. All of the financial ratios in this report are provided in a table in Appendix I.

Ratio Name	Ratio ID
Profitability	R1-R7
Operational efficiency	R8-R12
Management structure	R13-R17
Human resource management	R18-R21

Table 2: Group separation for Financial ratios

Data from the balance sheet and income statement are obtained after the initial categories have been identified and companies have been chosen. Due to the vast number of variables found to be relevant indicators of organisational problems in previous research, a list of 21 potentially valuable parameters (ratios) was collected for assessment. The parameters are divided into four regular ratio divisions, one of which is profitability, efficiency, management structure, and HR management. The ratios were selected based on their importance in the literature and possible relevance to the thesis.

In what methodology is concerned, it is important to specify the utilisation of the ratios. Financial ratios will help you understand financial statements. Investors and managers rely extensively on the knowledge obtained from financial data processing. We will employ four main categories of financial ratios: (1) Profitability, (2) Operational Efficiency, (3) Management Structure, and (4) Human Resource Management.

It is critical to note that by using financial ratios to measure a company's overall financial performance, more than one ratio may be considered while formulating an unbiased opinion. For example, a company's solvency ratios might be optimal, but if the ratios that help analyse production and operation are distorted, a quite different opinion is formed.

Bearing that explanation in mind, the ratios will support the probability of default, making it important to cover the analysis of profitability, efficiency, management structure, and HR management. As mentioned before, the independent variables were chosen based on the findings of other researchers too.

3.3 Logit Model

The Logit model is a probability within certain conditions methodology used to investigate the relationship between a set of features of a person (or company) and its proclivity to belong to previously defined classes (Lewis-Beck, 2004). As previously said, the basic feature of the logit model is that the dependent variable may only have a value of 0 or 1 (dichotomic variable[1]).

To determine the model parameters, the maximum likelihood approach[2] is used. Maximum likelihood estimation is one of the methods[3] created by statisticians for estimating the parameters in a mathematical model. This approach can be used to estimate both complex nonlinear and linear models.

Some multivariate statistical methods, such as discriminant regression, are used to estimate a dichotomous dependent variable from a variety of independent variables.

The linear discriminant analysis predicts the category to which the attribute corresponds - bankrupt / not bankrupt - directly. Even though it is an optimal prediction rule, this strategy includes the presumption of multivariate normality of the independent variables and variance matrices - covariance equals of both classes.

[1] The dependent variable is called dummy variable. Since they are commonly used to numerically describe a qualitative attribute of an object, dummy variables are often known as qualitative variables. Dummy variables are normally defined to take on one of a small number of integer values, with zero and one being the most common choices. In cross-sectional or time series regressions, dummy variables may be used.

[2] The maximum likelihood function estimates and associated standard errors of the regression coefficients in a logistic model are typically obtained by using computer packages for logistic regression. These statistics can then be used to obtain numerical values for estimate adjusted odds ratios, to test hypotheses and to obtain confidence intervals for population odds ratios based on standard maximum likelihood techniques.

[3] Another popular approach is least squares estimation. This approach as a method for estimating the parameters in a classical straight line or multiple linear regression mode. These two methods are different approaches that happen to give the same results for classical linear regression analyses when the dependent variable is assumed to be normally distributed.

In the logit model there are no restrictions about the normality of the explanatory variables. Therefore, it seems less restrictive to apply it. When applied to the Logit model, the main objective of the estimation of maximum Likelihood method is to find the value of the parameters β and σ^2 that maximise the probability given by likelihood function.

Thus, in the Logit model, the relation between the probability of a business failure (p) and the value of the financial ratios is a curve in S ranging between 0 and 1.

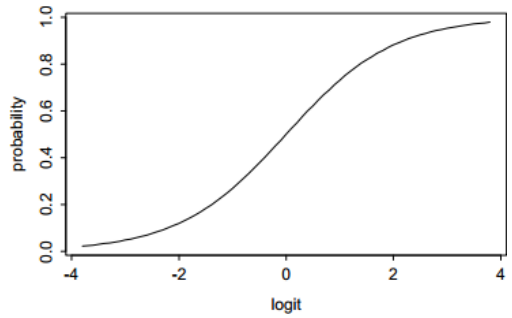

Figure 4: Logit transformation

The logistic model is well-known because it corresponds to the general sigmoid form of the logistic equation. Epidemiologists, for example, find sigmoid shapes especially enticing. If the vector Zi is interpreted as an index that incorporates the contributions of various risk factors, then F(Zi) represents the risk for a given value of Z. As a result, the risk is small for low Z values, increases over a spectrum of intermediate Z values, and stays close to one until Z is high enough.

A logit model's structure is based on a logistic cumulative probability function, which is defined as:

$$p_i = F(Z_i) = F\left(a + \sum\nolimits_j \beta_j * X_{ij}\right) = \frac{1}{1 + e^{-Zi}} = \frac{1}{1 + e^{-(a+\sum_j \beta_j * X_{ij})}}$$

Figure 5: Equation 1 - Logistic model

In which:

$$Z_i = \alpha + \sum\nolimits_j \beta_j * X_{ij}$$

Figure 6: Equation 2 - Logistic regression model

p_i: Probability of bankruptcy

i: Observation number

β_j: Coefficient for each of the independent variables

X: Ratios of economic-financial companies

The equation's parameters β define the rate of increase or decrease of the S-shaped curve for p(i). The parameter's sign shows whether the curve ascends (β > 0) or descends (β < 0), and the level of change increases as |β| increases.

The right-hand side of equation 1 simplifies to a constant when β = 0. The curve then becomes a horizontal straight line when p(i) is equal at all i.

Equation 1 is well-suited to modeling a probability since F(Zi) values range from 0 to 1 as varies from to $-\infty$ to $+\infty$.

The probability of bankruptcy is obtained through the product of the ratios and a Z index, which transforms the previous expression, allowing for a certain probability of bankruptcy. The explanatory variables with negative coefficients reduce the likelihood of bankruptcy by reducing $e^y$to zero. Similarly, positive coefficient independent variables increase the risk of bankruptcy.

The Logit methodology can present several problems:

- It requires that the groups that are clearly well separated;
- It requires that the explanatory variables are independent;

However, it also has some advantages:

- It does not imply that the dependent and independent variables have a linear relationship;
- Does not require the variables to conform to a normal distribution;
- It is more robust than discriminant analysis, since it is applicable other than the normal distribution;

- The dependent variable can be viewed as the likelihood of the company declaring bankruptcy;
- A visually appealing S-shaped illustration of the cumulative impact of many risk factors on the likelihood of an occurrence.

Figure 7 illustrates the Logit analysis decision process, which is divided into six stages. The procedure Logit Loglinear Analysis examines the relationship between dependent and independent variables. The dependent variables are categorical, while the independent variables are not. The weighted covariant mean of a value is added to it. A linear combination of parameters is used to represent the odds logarithm of the dependent variables.

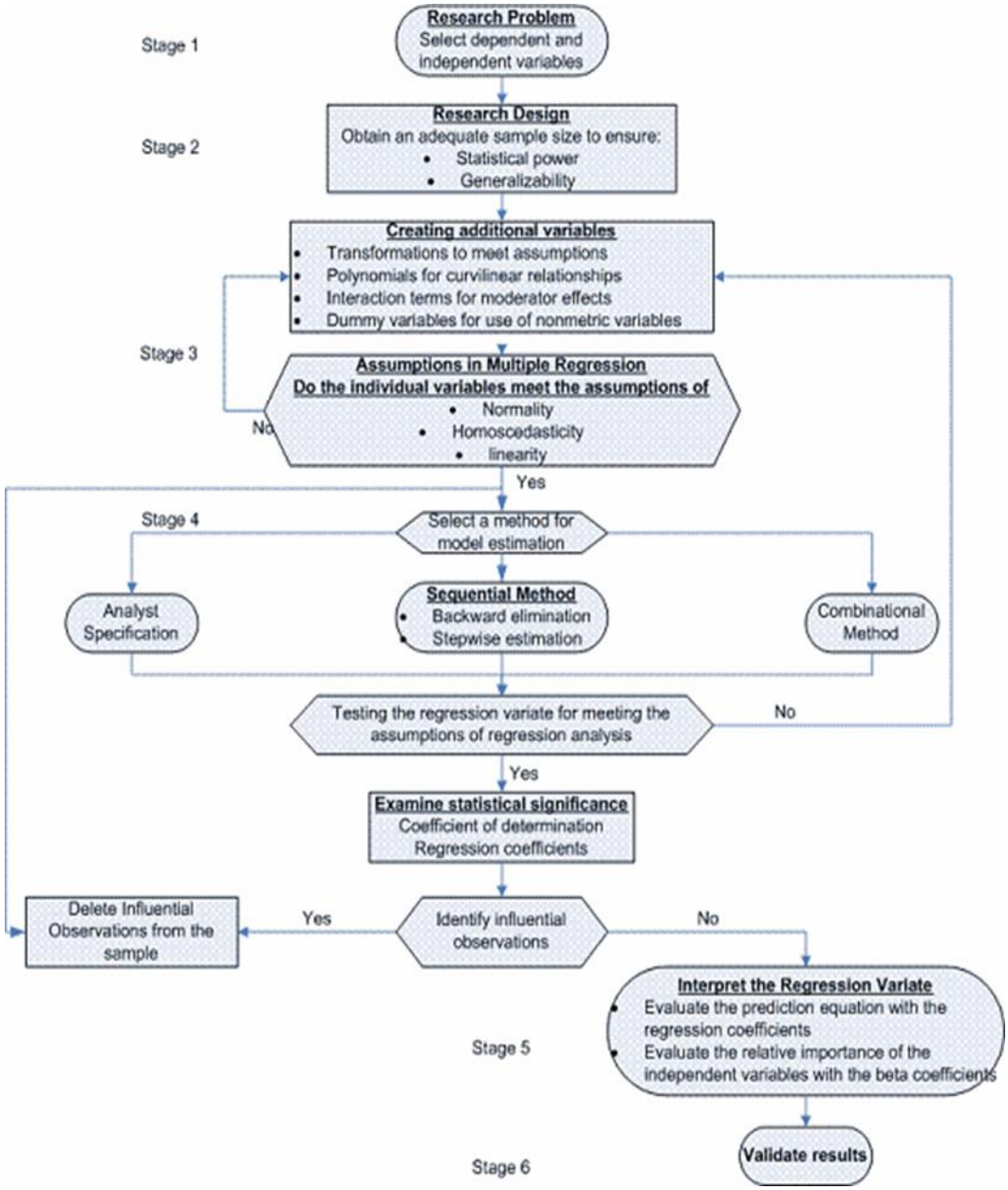

Figure 7: Decision process of Logit Analysis

(Source; Apply logit analysis in bankruptcy prediction, Ying Zhou and Taha M.S. Elhag, 17th, September 2017)

3.4 Misclassification costs

To evaluate the predictive ability of the predicted model, we use two forms of classification errors. The number of firms mistakenly identified as bankrupt is referred to as a Type I error,

while a Type II error means the reverse. In the first situation, the costs of misclassification will cover principal, interest, collection expenses, and legal expenses, while in the second scenario, the costs of deferred company sales are included. Since reducing the frequency of one type of error will maximise the frequency of the other, the optimal cut-off point is determined by the relative costs of the two types of errors. Type I error misclassification costs much more expensive than Type II error (Lee, 2002); (Thomas, L. C., Edelman, D. B. and Cook, J. N., 2002).

Various cut-off point metrics have been used in previous studies to measure misclassification costs and prediction model results. In this analysis, a cut-off point of 0.5 is used to achieve a fair classification rate as the optimum cut-off by decreasing Type I error such that less bankrupt firms go undetected (Chi, L C and Tang, T C, 2006).

4. EMPIRICAL STUDY AND DATA ANALYSIS

4.1 Independent sample t-test

The chi-square (x2) test of independence is used to investigate the interaction between two independent variables. Analysis of variance investigates the relationship between an independent variable and a dependent variable, correlation and regression investigate the relationship between two independent variables, and the chi-square (x2) test of independence investigates the relationship between two independent variables.

Table 3 shows the mean values of all variables in the model estimation sample's healthy and bankrupt groups. The table shows the individual sample t-test statistics and associated p values for the two groups. The p-value (2-tailed) can be used to test group variations:

- If the p-value (2-tailed) is equal or less than 0.05, the mean scores on categorical variables vary significantly between the two groups.
- If the p-value (2-tailed) is above 0.05, there is no statistically meaningful distinction between the two groups.

Table 3: Financial ratios of healthy and bankrupt firms

Ratio		Healthy	Bankrupt	T	p-	p-value 2-
ID	Name	mean	mean	statistic	value	tailed
R1	Return on shareholders fund	9.784261	-18.831783	-2.872	0.001	0.005
R2	Return on capital employed	16.246087	-2.843435	-2.692	0.035	0.008
R3	Return on total assets	4.000913	-3.880935	-3.279	0.004	0.001
R4	Cash flow/ turnover	4.891565	-3.402000	-2.840	0.000	0.006
R5	Profit margin	2.507804	-5.741913	-2.554	0.000	0.012
R6	EBITDA Margin	7.545500	1.592435	-2.132	0.001	0.036
R7	EBIT Margin	4.257957	-2.600500	-2.271	0.000	0.026
R8	Net asset turnover	4.042717	9.468783	1.308	0.011	0.194
R9	Interest cover	6.346848	11.210870	0.526	0.094	0.600
R10	Stock turnover	17.611848	39.448739	1.753	0.006	0.083
R11	Collection period	111.211674	148.406065	1.183	0.001	0.240
R12	Credit period	86.930783	137.430913	2.153	0.000	0.034

R13	Current ratio	1.314913	2.457087	1.191	0.031	0.237
R14	Liquidity ratio	0.934000	2.159413	1.313	0.038	0.192
R15	Shareholders liquidity ratio	23.196370	37.054891	0.715	0.342	0.476
R16	Solvency ratio	28.152804	16.253500	-2.100	0.000	0.039
R17	Gearing ratio	162.546565	194.625022	0.748	0.030	0.456
R18	Operating profit per employee	222.888389	246.195150	0.312	0.206	0.756
R19	Share funds per employee	52.971922	67.636093	1.176	0.080	0.243
R20	Working capital per employee	60.867111	40.227859	-1.242	0.933	0.218
R21	Total asset per employee	210.308991	259.182585	1.039	0.523	0.302

As a result, the two groups differ in nine ratios R1 (Return on shareholders fund), R2 (Return on capital employed), R3 (Return on total assets), R4 (Cash Flow/ Turnover), R5 (Profit Margin), R6 (EBITDA Margin), R7 (EBIT Margin), R12 (Credit period) and R16 (Solvency ratio).

The analysis of the means of profitability ratios of the two groups reveals that the bankrupt group had poorer profit generating potential prior to bankruptcy. The t-tests also show a large change in the operational performance ratio. Furthermore, the t-test results indicate that there are no significant variations between the two groups in terms of management organisation ratios and human capital ratios.

4.2 Estimation and model performance

Table 7 and Table 8 show the effects of the Logit Model with a cut-off point of 0.5. The Total Model Fit table illustrates the model's utility, while the Cox & Snell R square and Nagelkerke R values reflect the amount of difference in the dependent variable explained by the model. This range of variables explains 48.2% and 64.3% of the uncertainty, respectively, as seen in Table 4.

Table 4: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	67.015[a]	.482	.643

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

The Omnibus Tests of Model Coefficients (see Table 5) give an average measure of how well the model fits, also known as a goodness-of-fit test; all sig. in this table are less than 0.05, indicating that the approximate Logit model provides a good fit with the data and that the estimated variables' parameters are significant. The Hosmer and Lemeshow goodness-of-fit value (see Table 6) also supports the model as meaningful; sig. is 0.503 in this analysis with chi-square value 7.319 with 8 degrees of freedom, indicating that the final four-predictor model suits the results well so there is no substantial difference between the observed and forecast classifications.

Table 5: Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	60.524	21	.000
	Block	60.524	21	.000
	Model	60.524	21	.000

Table 6: Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.319	8	.503

The Variables Table 8 presents details about each predictor's contribution or significance. The Wald test, which is widely used to test the importance of the individual coefficient for each predictor in a Logit model (Hair, 1998), demonstrates the first four predictors with the most significant effects on the dependent variable.

The Logit forward stepwise method picked and maintained four predictors from 21 candidate variables that could better distinguish stable firms from bankrupt firms, with the significance level set at p-value=0.05.

- R4 (Cash flow/ turnover)
- R6 (EBITDA Margin)
- R8 (Net asset turnover)
- R12 (Credit period)

Table 7: Classification Table

Observed			Predicted		
			Bankrupt		Percentage Correct
			Bankrupt	Healthy	
Step 1	Bankrupt variable	Bankrupt	37	9	80.4
		Healthy	6	40	87.0
	Overall Percentage				83.7

a. The cut value is .500

Table 8: Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	R4	1.110	.488	5.168	1	.023	3.035	1.165	7.905
	R6	-.967	.465	4.327	1	.038	.380	.153	.946
	R8	-.162	.078	4.248	1	.039	.851	.730	.992
	R12	-.020	.009	4.391	1	.036	.980	.962	.999
	Constant	4.261	2.145	3.947	1	.047	70.884		

a. Variable(s) entered on step 1: R1, R2, R3, R4, R5, R6, R7, R8, R9, R10, R11, R12, R13, R14, R15, R16, R17, R18, R19, R20, R21.

Four variables from the initial set of 21 are chosen as doing the best overall job together in predicting corporate bankruptcy. This profile lacked any of the critical variables that could be calculated separately. The contribution of the different variables is measured, and since this is an iterative procedure, there is little proof that the resulting discriminant function is optimal. However, the feature outperforms the alternatives, which have multiple runs analysing various ratio profiles.

The B. values in the first column are used to measure the risk of a case collapsing into a particular type of output, either stable or bankrupt in this analysis. As a result, the Logit model for forecasting bankruptcy can be written in logit(y) as follows;

$$Logit(y) = 4.261 + 1.11 \times R_4 - 0.967 \times R_6 - 0.162 \times R_8 - 0.02 \times R_{12}$$

The likelihood ratios for each chosen indicator are represented by the values in the Exp (B) column. When the predictor's value increases by one unit, the odds ratio increases (or decreases if less than one) the chances of being in one outcome group. In this case, the odds ratio of stable firms is allocated as 1, the Cash flow/turnover is 3.035 times greater than that of distressed

firms, and all other predictors are kept steady. For each of the odds ratios, the 95% confidence interval (95% CI for Exp (B)) is seen in the last column, with a lower and upper limit.

The set of predictors selected by the forward stepwise method differs from the set of independent-sample t-test, from which a total of nine variables are derived. This does not mean that bankrupt firms differ from healthier firms in just these four predictors; rather, it merely implies that these four ratios combined will better differentiate the two groups.

This model employs major financial ratios in the fields of profitability and operating performance. According to this knowledge, the reasons for SMEs going bankrupt are as follows: (1) a decline in profit generating capacity; (2) inadequate working resources and loss of ability to pay interest, which contributes to more financial distress; and (3) a lack of maintaining relationships with clients, as demonstrated by the longer time for a firm's customer to grant credit.

4.3 Results of bankrupt companies

Analysing now the values for a sample of 46 insolvent companies, data are present below.

Table 9: Bankrupt companies' descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
R4	46	-68.3900	30.2240	-3.402000	18.8922472	-1.597	.350	3.319	.688
R6	46	-64.7000	36.3530	1.592435	17.7029980	-1.501	.350	4.279	.688
R8	46	.0010	138.7270	9.468783	27.6445688	4.320	.350	18.200	.688
R12	46	.0000	705.9580	137.430913	150.4500120	1.998	.350	4.299	.688
Valid N (listwise)	46								

Regarding the cash flow turnover mean, it is at -3.40. This ratio expresses how quick the company is going through its cash cycles to use cash towards better uses. It measures the overall company efficiency with its cash. We can see through the graph below, that there are more companies above the industry average. This means that just because a company has a high amount of earnings, but a poor amount of cash does not always mean that it is in a strong situation. Companies with low cash reserves, on the other hand, may require short-term funding to meet their commitments in the near future.

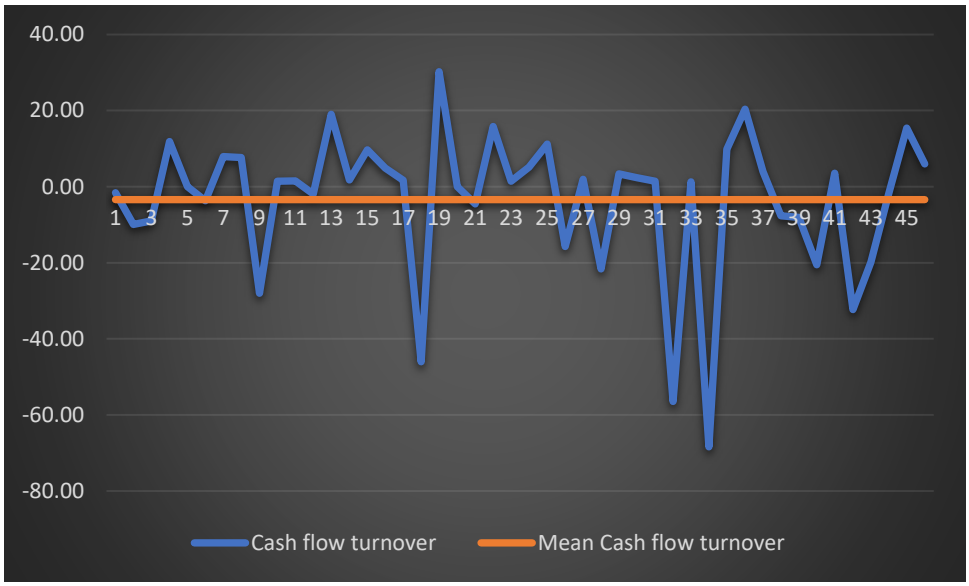

Figure 8: Bankrupt companies cash flow turnover

Regarding the net asset turnover mean, it is at 9.47. This ratio compares the worth of a company's earnings or profits to the worth of its properties. The net asset turnover is a calculation of how effectively a business uses its assets to produce sales. We can see through the graph below, that there are more companies below the industry average. This means that firms aren't making the best use of their money to raise revenue.

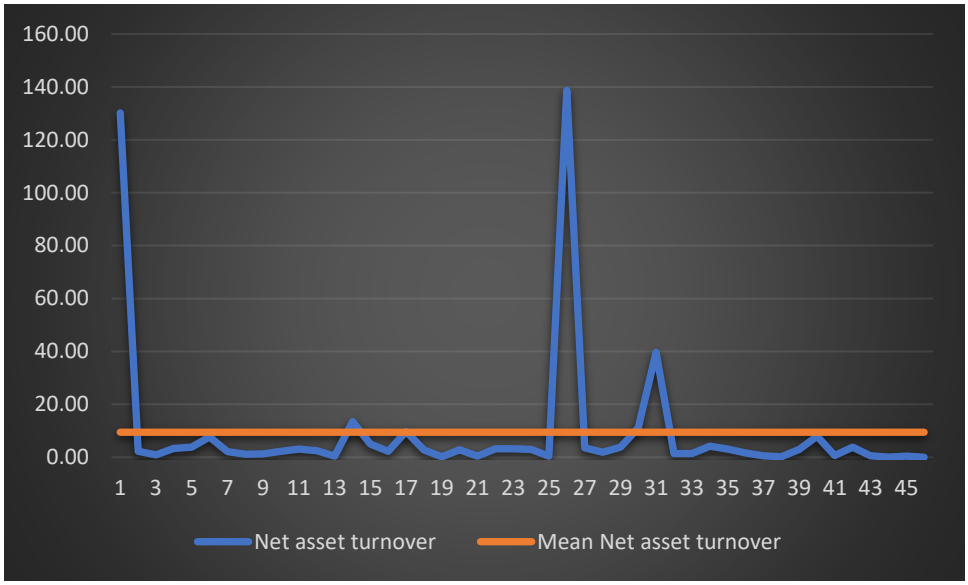

Figure 9: Bankrupt companies net asset turnover

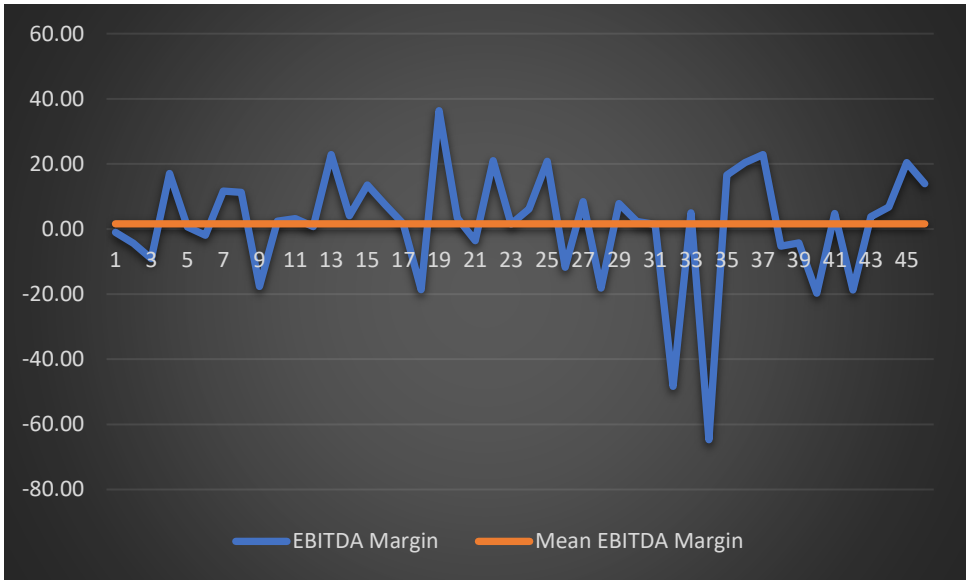

Figure 10: Bankrupt companies EBITDA margin

Regarding the EBITDA margin mean, it is at 1.59. This rate reflects a company's profits before debt, taxation, depreciation, and amortisation. It estimates gross operating profit as a percentage of sales. We can see through the graph below, that there are slightly more companies above the industry average but still this is relatively low. This means that corporations are

facing both sustainability and cash flow problems. A company's strong EBITDA does not always imply that it is profitable. This is because EBITDA lacks improvements in working capital, which is normally necessary for business growth. Furthermore, it does not take into account capital investments used to cover assets on the balance sheet.

Regarding the credit period mean, it is at 137.43. This percentage expresses how many days a customer should wait before paying an invoice. It determines how much operating capital a corporation is prepared to spend in its accounts receivable in order to produce revenue. We can see through the graph below, that there are more companies below the industry average. This means that companies are collecting payments faster. The disadvantage of this is that it could mean that the company's credit rules are too stringent, and consumers may seek out vendors or service providers with more favourable payment terms.

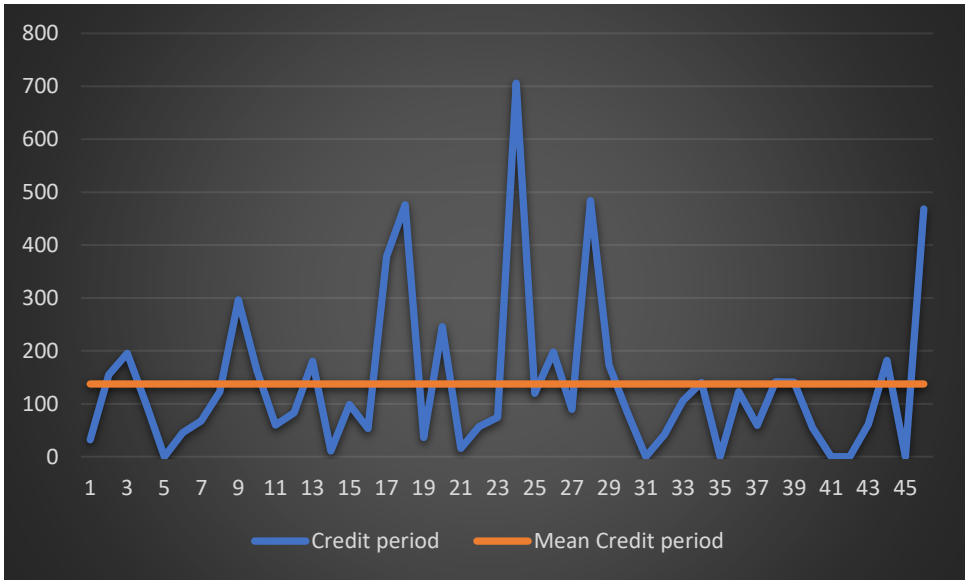

Figure 11: Bankrupt companies credit period

4.4 Results of healthy companies

Analysing now the values for a sample of 46 healthy companies, data are present below.

Table 10: Healthy companies' descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
R4	46	-9.5910	27.5380	4.891565	5.9551547	1.261	.350	4.626	.688
R6	46	-6.5010	29.5980	7.545500	6.7349272	1.234	.350	3.179	.688
R8	46	.6670	30.7300	4.042717	5.1899838	3.702	.350	16.075	.688
R12	46	9.5250	327.8550	86.930783	51.7301298	2.229	.350	9.439	.688
Valid N (listwise)	46								

Observing now the mean of each independent variable, and focusing primarily in the values obtained, for the ratios of healthy companies, we can conclude that the average values are all positive but not very close to zero. When it comes to the analysis of companies considered healthy, it makes sense that this value is positive or close to zero.

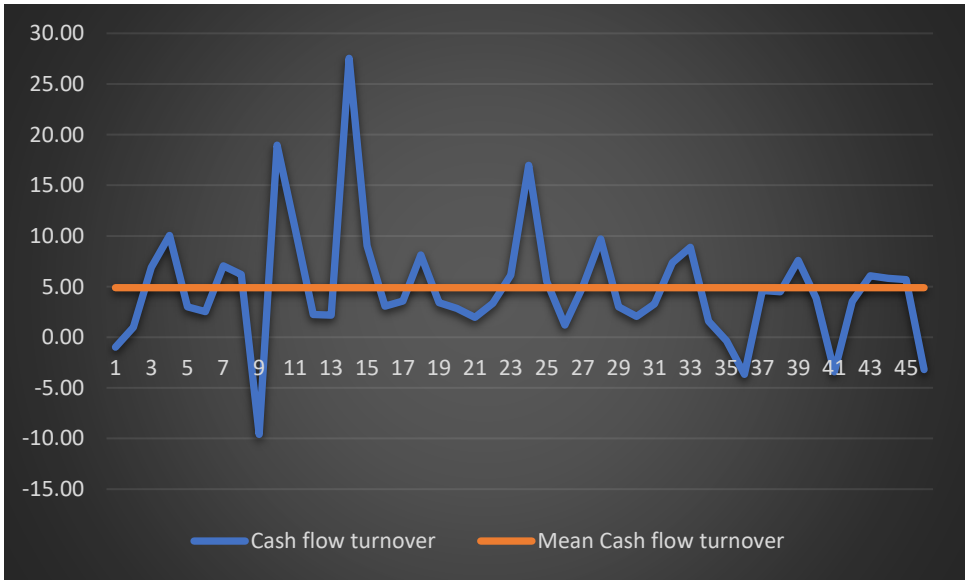

Figure 12: Healthy companies cash flow turnover

Regarding the cash flow turnover mean, it is at 4.89. As mentioned earlier, this ratio expresses how quick the company is going through its cash cycles to use cash towards better uses. It measures the overall company efficiency with its cash. We can see through the graph below, that there are more companies are almost split equally above and below the industry average with a positive sign. This means that most of the companies are having high cash turnover which indicates a greater frequency of cash replenishment through revenue.

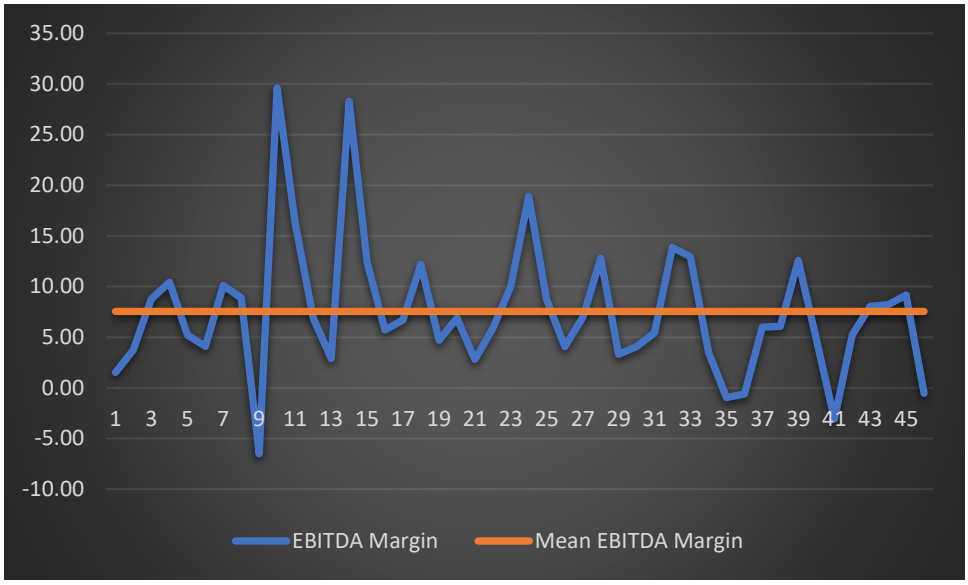

Figure 13: Healthy companies EBITDA margin

Regarding the EBITDA margin mean, it is at 7.55, much higher from the insolvent companies. As mentioned earlier, this ratio reflects a company's profits before debt, taxation, depreciation, and amortisation. It estimates gross operating profit as a percentage of sales. We can see through the graph below, that there are slightly more companies below the industry average but still close to the industry mean. This means that companies have profitability issues as wells as issues with cash flow. The positive EBITDA implies that the company earning are stable but is still relatively low with most of the companies below the 7.55%. Profitability and cash flow issues are indicative of a low EBITDA margin. This is because EBITDA lacks improvements in working capital, which is normally necessary for business growth. Furthermore, it does not take into account capital investments used to cover assets on the balance sheet.

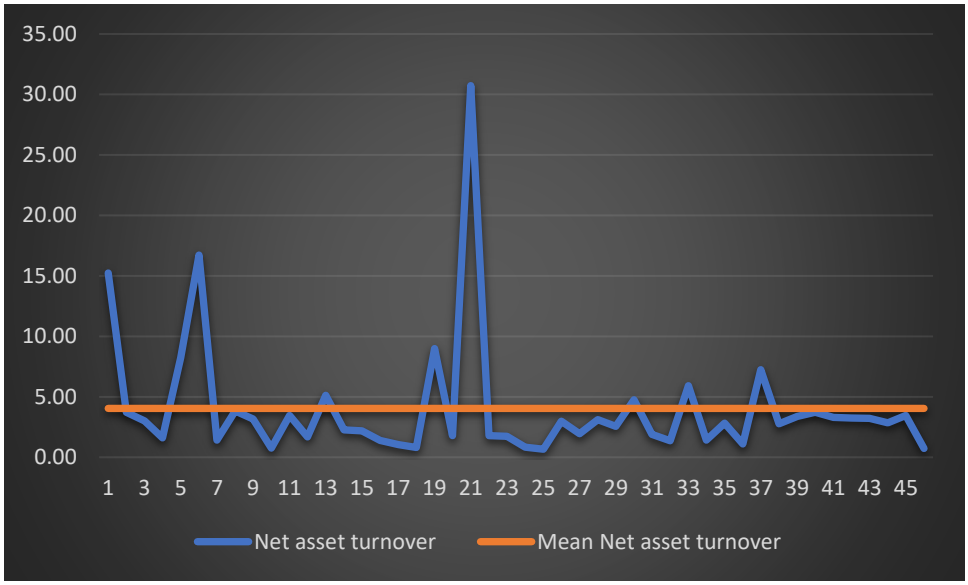

Figure 14: Healthy companies net asset turnover

Regarding the net asset turnover mean, it is at 4.04. As mentioned earlier, this ratio compares the worth of a company's earnings or profits to the worth of its properties. The net asset turnover is a calculation of how effectively a business uses its assets to produce sales. We can see through the graph below, that there are more companies below the industry average but still with a positive sign. This means that most firms are not using efficiently their assets to generate revenue or a potential for sales is not maximised. On the other hand, companies located above average convey that they have excess capital when compared to their real needs.

Regarding the credit period mean, it is at 86.93, significantly lower than the insolvent companies. As already mentioned, this percentage expresses how many days a customer should wait before paying an invoice. It determines how much operating capital a corporation is prepared to spend in its accounts receivable in order to produce revenue. We can see through the graph below, that there are more companies below the industry average. This means that companies are collecting payments faster. The disadvantage of this is that it could mean that the company's credit rules are too stringent, and consumers may seek out vendors or service providers with more favourable payment terms. The impressive thing about it is that healthy companies are collecting payments faster than the insolvent or distressed companies.

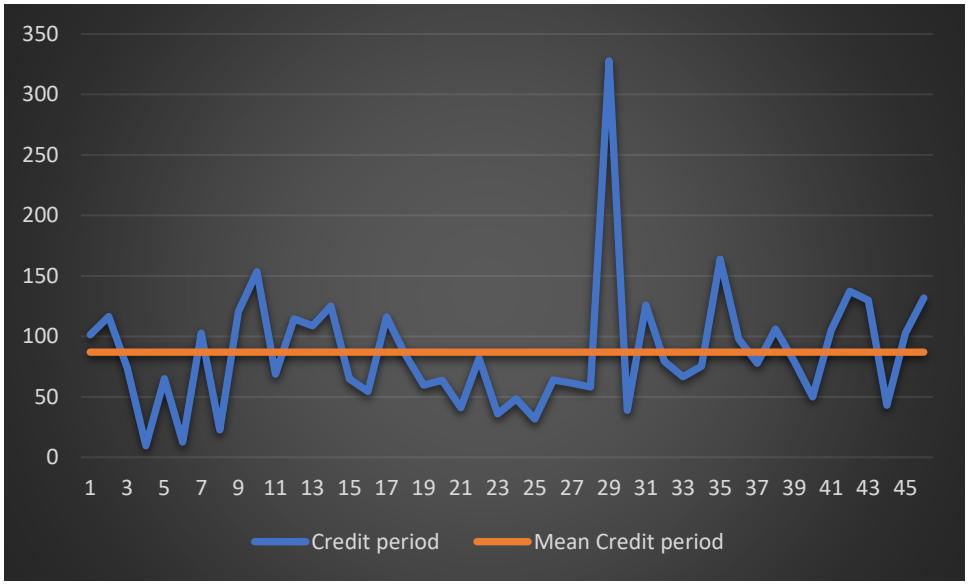

Figure 15: Healthy companies credit period

4.5 Correlation of the sample variables

Starting now to examine the correlation among the predictor variables, it is apparent that there is no significant correlation between the ratios.

Looking to Table 11, it's possible to see that there are coefficients statistically significant to 1% and 5%. We can observe moderate correlation when Cash flow/turnover vs EBITDA Margin. With the help of SPSS, we achieve the Pearson correlation of 0.952. These correlations are statistically significant for a 1% significance level.

Table 11: Correlations

		R4	R6	R8	R12
R4	Pearson Correlation	1	.952**	-.102	-.210*
	Sig. (2-tailed)		.000	.331	.044
	N	92	92	92	92
R6	Pearson Correlation	.952**	1	-.146	-.167
	Sig. (2-tailed)	.000		.165	.112
	N	92	92	92	92
R8	Pearson Correlation	-.102	-.146	1	-.038
	Sig. (2-tailed)	.331	.165		.717
	N	92	92	92	92

R12	Pearson Correlation	-.210*	-.167	-.038	1
	Sig. (2-tailed)	.044	.112	.717	
	N	92	92	92	92

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Turns out obvious that must exist some correlation between these ratios because they are profitability and efficiency ratios. These two ratios are all related since they "server the same purpose", if we have high cash flow turnovers this means that the firm's cash periods are moving quickly (i.e. capable of easily replenishing it and putting cash to greater use), hence being efficient and consequently a high operating profit.

Based on the previous table, we find that with a Pearson coefficient of -0.210 for Cash flow/ turnover vs Credit period. This correlation is statistically significant for a 5% significance level. Considering all negative correlations, only the above mentioned is 5% statistically significant. All the other explanatory variables didn't show a statically significant level.

5. CONCLUSIONS AND RECOMMENDATIONS

In times when companies are facing increasing difficulties, it is pertinent to resort to the creation of mechanisms that detect whether a company is or is not tending to insolvency.

In this context, the aim of this thesis was to analyse Greek SME industry that was experiencing a situation of great fragility in the Greek economic recessions period.

This study established a four-variable Logit model to forecast bankruptcy for Greek SMEs; with a cut-off point of 0.5, the overall prediction accuracy is 83%. According to the sample t test results, the bankrupt group of firms has a lower profit generating capacity prior to bankruptcy, and there is a substantial gap in the operational efficiency ratio.

Although the set of predictors chosen by the forward stepwise method differs from the set chosen by the sample t test, the overall success of the logit model shows that the predictors, which stand for business profitability, organisational quality, and human capital management, is clearly distinguished between stable and bankrupt companies. Based on the findings of the analysis, it can be assumed that the causes of bankruptcy in the Greek industry may be (1) a reduction in profit generating capacity; (2) inadequate working resources and loss of ability to pay interest; (3) a lack of controlling customer relationships; and (4) a relatively slow collection mechanism, weak credit practices, or consumers that are not financially sustainable or savvy.

This research does have certain drawbacks. First and foremost, due to the lack of data from the failing company, the out of sample test is not included in this analysis. Furthermore, while recent literature indicates the importance of non-financial ratio details in bankruptcy prediction, such as firm basic characteristics (size, age, capital investments, and depreciation) and country risk controls, this analysis only sampled firms' financial ratios as predictors. The study implies that incorporating non-financial ratio knowledge from the survey firm into future research would boost the predictive performance of Logit analysis in bankruptcy prediction.

To sum up, we believe the analysis conducted helps to determine the warning signs of insolvency, as well as delivers information on the position of each company in terms of risk of insolvency.

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7. APPENDICES

Appendix I: Financial ratios calculation

Profitability ratios		
R1	Return on shareholders fund	(PLBT/SHFD)*100
R2	Return on capital employed	((PLBT+INTE)/(SHFD+NCLI)*100
R3	Return on total assets	(PLBT/TOAS)*100
R4	Cash flow/ turnover	(CF/OPRE)*100
R5	Profit margin	(PLBT/OPRE)*100
R6	EBITDA Margin	((EBIT+DEPR)/OPRE)*100
R7	EBIT Margin	(EBIT/OPRE)*100
Operational efficiency		
R8	Net asset turnover	OPRE/(SHFD+NCLI)
R9	Interest cover	OPPL/INTE
R10	Stock turnover	OPRE/STOK
R11	Collection period	(DEBT/OPRE)*360
R12	Credit period	(CRED/OPRE)*360
Management Structure ratios		
R13	Current ratio	CUAS/CULI
R14	Liquidity ratio	(CUAS-STOK)/CULI
R15	Shareholders liquidity ratio	SHFD/NCLI
R16	Solvency ratio	(SHFD/TOAS)*100
R17	Gearing ratio	((NCLI+LOAN)/SHFD)*100
Human Resource Management		
R18	Operating profit per employee	OPRE/EMPL
R19	Share funds per employee	SHFD/EMPL
R20	Working capital per employee	WKCA/EMPL
R21	Total asset per employee	WKCA/EMPL

Appendix II: Independent Samples Test (T-Test)

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
R1	Equal variances assumed	12.646	.001	-2.872	90	.005	-28.6160435	9.9631636	-48.4096070	-8.8224800
	Equal variances not assumed			-2.872	58.580	.006	-28.6160435	9.9631636	-48.5552790	-8.6768080
R2	Equal variances assumed	4.597	.035	-2.692	90	.008	-19.0895217	7.0917205	-33.1784623	-5.0005812
	Equal variances not assumed			-2.692	65.785	.009	-19.0895217	7.0917205	-33.2494638	-4.9295797
R3	Equal variances assumed	8.921	.004	-3.279	90	.001	-7.8818478	2.4034998	-12.6568198	-3.1068759
	Equal variances not assumed			-3.279	63.079	.002	-7.8818478	2.4034998	-12.6847417	-3.0789540
R4	Equal variances assumed	18.930	.000	-2.840	90	.006	-8.2935652	2.9206196	-14.0958858	-2.4912446
	Equal variances not assumed			-2.840	53.855	.006	-8.2935652	2.9206196	-14.1494158	-2.4377147
R5	Equal variances assumed	19.606	.000	-2.554	90	.012	-8.2497174	3.2295580	-14.6657980	-1.8336368
	Equal variances not assumed			-2.554	55.971	.013	-8.2497174	3.2295580	-14.7193730	-1.7800618
R6	Equal variances assumed	12.193	.001	-2.132	90	.036	-5.9530652	2.7926744	-11.5012003	-.4049302
	Equal variances not assumed			-2.132	57.759	.037	-5.9530652	2.7926744	-11.5437073	-.3624231
R7	Equal variances assumed	19.790	.000	-2.271	90	.026	-6.8584565	3.0197561	-12.8577291	-.8591840
	Equal variances not assumed			-2.271	56.012	.027	-6.8584565	3.0197561	-12.9077274	-.8091856
R8	Equal variances assumed	6.711	.011	1.308	90	.194	5.4260652	4.1471785	-2.8130287	13.6651592
	Equal variances not assumed			1.308	48.168	.197	5.4260652	4.1471785	-2.9116438	13.7637742
R9	Equal variances assumed	2.861	.094	.526	90	.600	4.8640217	9.2419200	-13.4966655	23.2247090
	Equal variances not assumed			.526	50.521	.601	4.8640217	9.2419200	-13.6941746	23.4222181
R10	Equal variances assumed	8.011	.006	1.753	90	.083	21.8368913	12.4573922	-2.9118925	46.5856751
	Equal variances not assumed			1.753	67.816	.084	21.8368913	12.4573922	-3.0226660	46.6964487
R11	Equal variances assumed	11.025	.001	1.183	90	.240	37.1943913	31.4365001	-25.2597031	99.6484857
	Equal variances not assumed			1.183	68.607	.241	37.1943913	31.4365001	-25.5261215	99.9149041
R12	Equal variances assumed	16.219	.000	2.153	90	.034	50.5001304	23.4572750	3.8981595	97.1021014
	Equal variances not assumed			2.153	55.493	.036	50.5001304	23.4572750	3.5000942	97.5001666
R13	Equal variances assumed	4.824	.031	1.191	90	.237	1.1421739	.9591047	-.7632550	3.0476028
	Equal variances not assumed			1.191	45.553	.240	1.1421739	.9591047	-.7889150	3.0732628
R14	Equal variances assumed	4.414	.038	1.313	90	.192	1.2254130	.9330856	-.6283244	3.0791505
	Equal variances not assumed			1.313	45.575	.196	1.2254130	.9330856	-.6532636	3.1040897
R15	Equal variances assumed	.913	.342	.715	90	.476	13.8585217	19.3781662	-24.6395876	52.3566311
	Equal variances not assumed			.715	88.501	.476	13.8585217	19.3781662	-24.6484735	52.3655170
R16	Equal variances assumed	15.807	.000	-2.100	90	.039	-11.8993043	5.6675590	-23.1588994	-.6397092
	Equal variances not assumed			-2.100	53.843	.040	-11.8993043	5.6675590	-23.2628358	-.5357729
R17	Equal variances assumed	4.865	.030	.748	90	.456	32.0784565	42.8776854	-53.1055493	117.2624624
	Equal variances not assumed			.748	80.437	.457	32.0784565	42.8776854	-53.2437376	117.4006506
R18	Equal variances assumed	1.624	.206	.312	90	.756	23.3067613	74.7009117	-125.0996381	171.7131608
	Equal variances not assumed			.312	65.332	.756	23.3067613	74.7009117	-125.8669008	172.4804235
R19	Equal variances assumed	3.142	.080	1.176	90	.243	14.6641710	12.4737936	-10.1171972	39.4455392
	Equal variances not assumed			1.176	77.192	.243	14.6641710	12.4737936	-10.1733373	39.5016793
R20	Equal variances assumed	.007	.933	-1.242	90	.218	-20.6392524	16.6203811	-53.6585404	12.3800357
	Equal variances not assumed			-1.242	87.053	.218	-20.6392524	16.6203811	-53.6737736	12.3952689
R21	Equal variances assumed	.411	.523	1.039	90	.302	48.8735931	47.0556338	-44.6106365	142.3578227
	Equal variances not assumed			1.039	89.403	.302	48.8735931	47.0556338	-44.6191362	142.3663224

Appendix III: Group Statistics (T-Test)

Group Statistics

	Bankrupt	N	Mean	Std. Deviation	Std. Error Mean
R1	Bankrupt	46	-18.831783	62.8899230	9.2726133
	Healthy	46	9.784261	24.7190318	3.6446224
R2	Bankrupt	46	-2.843435	43.1106607	6.3563201
	Healthy	46	16.246087	21.3289923	3.1447883
R3	Bankrupt	46	-3.880935	14.8211737	2.1852628
	Healthy	46	4.000913	6.7872040	1.0007186
R4	Bankrupt	46	-3.402000	18.8922472	2.7855099
	Healthy	46	4.891565	5.9551547	.8780397
R5	Bankrupt	46	-5.741913	20.6625268	3.0465234
	Healthy	46	2.507804	7.2692533	1.0717929
R6	Bankrupt	46	1.592435	17.7029980	2.6101647
	Healthy	46	7.545500	6.7349272	.9930108
R7	Bankrupt	46	-2.600500	19.3161919	2.8480171
	Healthy	46	4.257957	6.8084774	1.0038552
R8	Bankrupt	46	9.468783	27.6445688	4.0759693
	Healthy	46	4.042717	5.1899838	.7652214
R9	Bankrupt	46	11.210870	60.8365004	8.9698526
	Healthy	46	6.346848	15.0970917	2.2259447
R10	Bankrupt	46	39.448739	74.9046184	11.0440835
	Healthy	46	17.611848	39.0881392	5.7632317
R11	Bankrupt	46	148.406065	188.2083591	27.7498086
	Healthy	46	111.211674	100.1862083	14.7716505
R12	Bankrupt	46	137.430913	150.4500120	22.1826441
	Healthy	46	86.930783	51.7301298	7.6271915
R13	Bankrupt	46	2.457087	6.4850688	.9561712
	Healthy	46	1.314913	.5083758	.0749559
R14	Bankrupt	46	2.159413	6.3083730	.9301189
	Healthy	46	.934000	.5042541	.0743482
R15	Bankrupt	46	37.054891	86.6761573	12.7797022
	Healthy	46	23.196370	98.7970478	14.5668300
R16	Bankrupt	46	16.253500	36.6633859	5.4057213
	Healthy	46	28.152804	11.5486998	1.7027629
R17	Bankrupt	46	194.625022	238.4644966	35.1596719
	Healthy	46	162.546565	166.4496781	24.5416661
R18	Bankrupt	46	246.195150	455.2039354	67.1161587
	Healthy	46	222.888389	222.4405153	32.7970647
R19	Bankrupt	46	67.636093	70.9676418	10.4636079
	Healthy	46	52.971922	46.0541865	6.7903193
R20	Bankrupt	46	40.227859	72.0038880	10.6163941
	Healthy	46	60.867111	86.7314550	12.7878554
R21	Bankrupt	46	259.182585	234.7073665	34.6057132
	Healthy	46	210.308991	216.2571501	31.8853772

Appendix IV: Variables in the Equation (Logistic regression)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	R1	.057	.033	2.988	1	.084	1.059	.992	1.130
	R2	-.025	.048	.260	1	.610	.976	.888	1.072
	R3	.125	.130	.919	1	.338	1.133	.878	1.462
	R4	1.110	.488	5.168	1	.023	3.035	1.165	7.905
	R5	-.565	.528	1.147	1	.284	.568	.202	1.599
	R6	-.967	.465	4.327	1	.038	.380	.153	.946
	R7	.386	.521	.548	1	.459	1.471	.530	4.085
	R8	-.162	.078	4.248	1	.039	.851	.730	.992
	R9	-.007	.009	.547	1	.460	.993	.975	1.011
	R10	-.018	.013	1.798	1	.180	.982	.957	1.008
	R11	.005	.007	.522	1	.470	1.005	.991	1.019
	R12	-.020	.009	4.391	1	.036	.980	.962	.999
	R13	.541	1.791	.091	1	.763	1.718	.051	57.519
	R14	-2.283	2.005	1.296	1	.255	.102	.002	5.189
	R15	-.004	.005	.900	1	.343	.996	.987	1.005
	R16	.041	.045	.831	1	.362	1.042	.954	1.138
	R17	.006	.005	1.536	1	.215	1.006	.997	1.015
	R18	.003	.003	.907	1	.341	1.003	.997	1.009
	R19	-.018	.014	1.618	1	.203	.982	.955	1.010
	R20	.003	.009	.098	1	.755	1.003	.985	1.021
	R21	.000	.004	.016	1	.898	1.000	.993	1.008
	Constant	4.261	2.145	3.947	1	.047	70.884		

a. Variable(s) entered on step 1: R1, R2, R3, R4, R5, R6, R7, R8, R9, R10, R11, R12, R13, R14, R15, R16, R17, R18, R19, R20, R21.

Appendix V: Contingency Table for Hosmer and Lemeshow Test (Logistic Regression)

Contingency Table for Hosmer and Lemeshow Test

		Bankrupt = Bankrupt		Bankrupt = Healthy		
		Observed	Expected	Observed	Expected	Total
Step 1	1	9	9.000	0	.000	9
	2	9	8.977	0	.023	9
	3	9	8.066	0	.934	9
	4	6	6.454	3	2.546	9
	5	6	4.801	3	4.199	9
	6	1	3.605	8	5.395	9
	7	3	2.782	6	6.218	9
	8	1	1.298	8	7.702	9
	9	1	.757	8	8.243	9
	10	1	.259	10	10.741	11

Appendix VI: Variables not in the Equation (Logistic regression)

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	R1	7.725	1	.005
		R2	6.855	1	.009
		R3	9.820	1	.002
		R4	7.565	1	.006
		R5	6.219	1	.013
		R6	4.422	1	.035
		R7	4.987	1	.026
		R8	1.717	1	.190
		R9	.282	1	.595
		R10	3.037	1	.081
		R11	1.409	1	.235
		R12	4.506	1	.034
		R13	1.427	1	.232
		R14	1.730	1	.188
		R15	.520	1	.471
		R16	4.296	1	.038
		R17	.569	1	.451
		R18	.099	1	.753
		R19	1.391	1	.238
		R20	1.550	1	.213
		R21	1.090	1	.297
	Overall Statistics		31.811	21	.061